A Mathematical Theory of Identification for Information Fusion

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Abstract

This paper applies Shannon theory, which was established to describe a discrete general communications system, to a general identification system that is affected by noise (and jamming), the probability of a discrete event occurring (such as an object in a certain region of space), and most importantly, the entropy and dissonance of the information source. This paper analyzes the cause of the many identification problems currently in the military from a fundamental information perspective. This includes analysis on how sharing information derived from Identification Friend-or-Foe (IFF), Electronic Support Measures (ESM), and Non-Cooperative Target Recognition (NCTR) sensors, with measures of information completeness and conflict, between varied military participants is essential for achieving a network-centric integrated identification picture.

1. Introduction

Over 50 years ago the seminal paper "A Mathematical Theory of Communication" laid the foundation of communications theory [Shannon, 1948]. Claude Shannon, while at Bell Labs in 1948, developed his theories of communication based on the work of Nyquist and Hartley who preceded him by twenty years by including the effects of noise in a channel and the statistical nature of transmitted signals. This paper extends his analysis of communications system properties to identification techniques and methodologies.

Shannon defines the fundamental problem of communications as "that of reproducing at one point either exactly or approximately a message selected at another point." Further he states that the messages "refer to or are correlated according to some system with certain physical or conceptual entities." For a subsurface, surface, airborne, or space-based object (which will henceforth just be described by the word "object"), the following correspondence definition can be made:

Correspondence 1

> ***Identification*** *of an object using some form of sensor information is the process of reproducing either exactly or approximately that object at another point.*

Shannon's *message* in an identification context is the information received from a sensor (or sensors) that describes an object with certain physical traits. Examples include whether the object has the intrinsic characteristics of rotors or fixed wings, a classifiable type of radar or communications system, a categorical thermal image, etc. For identification purposes, the information in a message contains features that allow attributes to be assigned to an unknown object that can be used to form an abstraction of the object at some level of approximation. Thus the use of the term "identification" refers to a taxonomic identification that describes what an object is (F/A-18, etc.) as opposed to its relationship to the identifying platform (Friend, Hostile, etc.). For most types of objects, the complete set of possible attributes that can be derived is dependent on the number, quality, and type of sensor information providers assigned to the identification task. In essence, whether a detected object can be classified as an aircraft or ship, bomber or airliner, B1 or 747, etc., is dependent on these sensor characteristics and their ability to form the abstraction. This relates identification to a communications link that will vary in effectiveness depending on its fidelity and number of paths. This leads to a second correspondence definition:

Correspondence 2

> *Each identification message that is received from a sensor is one that is selected from a set of possible identification messages, which can describe one or more possible objects or set of objects depending on the information content of the message.*

The number of possible messages is finite because the number of possible objects that can be reproduced by a sensor is also finite. So the selection of one message can be regarded as a *measure of the amount of information produced about an object when all choices are otherwise equiprobable*. This is significant because it allows an assessment of whether enough information exists to adequately describe an object, based on the number and types of identification messages. The measure of *information content* is what enables an automated process or human operator to determine if enough information exists to make a decision. A derivative of the Shannon information entropy measurement, which is described later in this paper, is used to measure the information content of a message or series of messages.

2. The Identification System

The one-way Shannon communication system is schematically represented in figure 1, with modifications to incorporate elements of the sensor domain for identification[1].

[1] All information associated with Shannon is reproduced or derived from reference [Shannon, 1948].

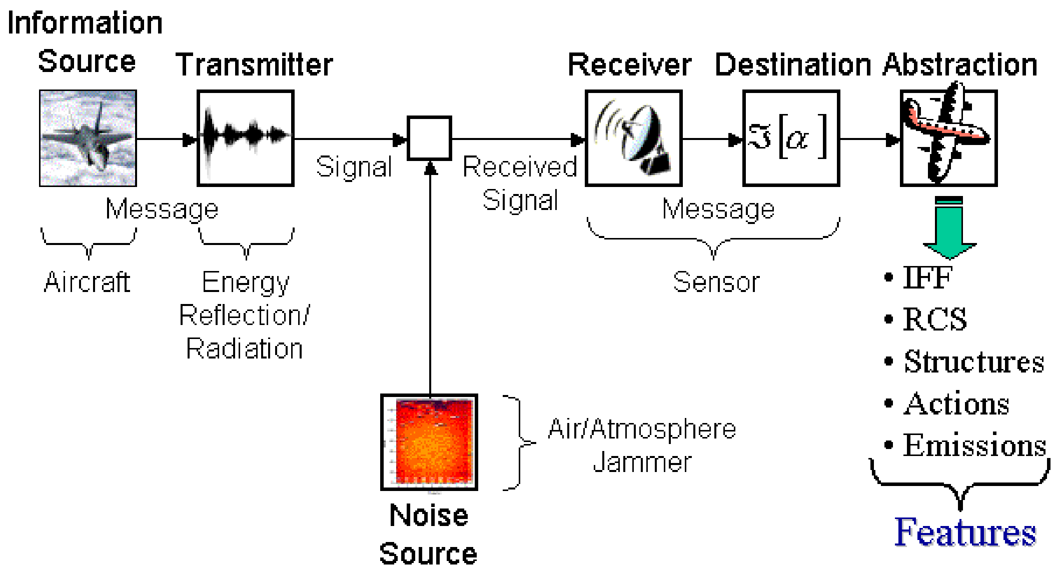

Figure 1. One-Way Diagram of a General Identification System Process

Referencing figure 1, the five parts can be described as follows:

1. An information source corresponds to something that either produces or reflects energy that is captured by a receiver and consists of a series of deterministic entities such as reflected spectra or electromagnetic emissions. For identification, the information source can provide multiple channels of information (often orthogonal) that can be correlated. The three information domains consist of Identification Friend-or-Foe (IFF), Electronic Support Measures (ESM), and Non-Cooperative Target Recognition (NCTR). IFF is considered cooperative communication because the information source willingly discloses information about itself to a requestor. ESM is considered to be unintentional cooperation because the information source, in the course of its normal operations, unknowingly discloses information about its identity based on the characteristics of its emissions. NCTR requires no cooperation from an information source other than its existence in order to derive features associated with its identity. Each of these sources can be considered as a unique discrete function $f_n[t]$, $g_n[t]$, and $h_n[t]$ where the subscript, n, indicates multiple sensor types from each information domain of IFF, ESM, and NCTR respectively. Each of these functions forms an *identification vector* that contributes to the generation of the *abstraction* of the original information source. This is illustrated with the series of features (similar to information domains) of a famous celebrity shown in figure 2 (derived from [Haak, 2002] and [Hall, 2001]).

Figure 2. Abstracted Information Features

Each set of features in figure 2 represents different information types at similar levels of abstraction (in this case). Each of these features can be considered as part of an identification vector for the image (caricature) shown in figure 3.

Figure 3. Correlated Information Features (Identification Vector)

Figure 3, in turn, is almost universally recognized as an abstraction of the photo of Bob Hope (the object) in figure 4.

Figure 4. Bob Hope (object)

In this example, the human brain fuses these feature vectors in order to determine the identity of the object. Notice that not all of the information about the object (Bob Hope) is present in figure 2 (there is no information abstraction of the ear). The assembled feature identification vectors in figure 3, even though they are an exaggerated abstraction of the object Bob Hope, can just as clearly represent him as the more representative photo in figure 4.

2. A transmitter is equivalent to an apparatus that emits some sort of radiation, or it could be a structure reflecting radiation back to a receiver. For IFF this is the transmitter of the transponder emitting a reply. For ESM this is the radiation of either radar or communications system emissions. For NCTR this could be radar, infra-red (IR) or a

similar emissions being radiated or reflected. All of these domains could be transmitted simultaneously or asynchronously.

3. The channel is the medium used to carry the information from the transmitter to the receiver. This is the atmosphere for airborne, space, and surface objects and water for undersea (and surface) objects. Noise sources also exist that change the channel characteristics and include target noise, atmospheric noise, space noise, random charge noise, etc. In a tactical environment there also exists the possibility of intentional channel modification or destruction in the form of spoofing or jamming.

4. The receiver is the device used for converting the transmitted or reflected energy from the information source and passing it on to a destination. Each set of ID sensor information, IFF, ESM, and NCTR has a unique receiver type optimized to extract signal energy in its respective domain.

5. The destination is the process that gathers the information from the information source via the receiver and processes it in order to extract the feature vector. This is generally the processing performed within the sensor that results in a “message” about the information source. In the example using the caricature of Bob Hope, one sensor type might extract the “hairline”, while another type might extract the “chin”, and still another his distinctive “nose”.

3. Forming the Identification Vector

For each sensor information domain, the communications system is slightly different. In the case of Mk XII ATCRBS IFF there are two versions of figure 1, one each for the uplink and downlink at 1030 and 1090 MHz respectively. For ESM there is a single channel where an object emits a signal from radar, sonar, or a communications system, which is the information source that provides the sensor with its input. For NCTR, the paths are generally the same (with the exception of infra-red which is a single path like ESM) with the return path of the most interest because it contains the feature information of interest to the destination processing. Each of these supports the formation of the object abstraction through some sort of fusion process.

Regardless of the source of information, just like the principles from Shannon’s discrete noiseless channel system, there exists a sequence of choices from a finite set of possibilities that can make up a possible object. For Mk XII IFF it is the set of possible reply codes (such as 4096 Mode 3/A octal codes). For ESM it is the set of all possible emitters that can be correlated to a physical object. For NCTR a similar set of features can be correlated to physical objects. Each of these choices is defined by a series of unique parameters (Shannon “symbols”), S_i that are defined by their domain. As an example for ESM, S_i could describe one of a couple of dozen possible parameters related to frequency, pulse width, PRF, etc. If the set of all possible sequences of parameters S_i, $\{S_1,\ldots,S_n\}$ is known and its elements have duration $t_1,\ldots,t_n$ then the total number of sequences $N(t)$ is,

$$N(t)=N(t-t_1)+N(t-t_2)+\ldots+N(t-t_n) \tag{1}$$

which defines the channel capacity, C,

$$C = \lim_{T \to \infty} \frac{\log N(T)}{T} \tag{2}$$

where T = the duration of the signals.

Following Shannon's pattern, we can consider an information source, how it can be described mathematically, and how much information is produced. In effect, statistical knowledge about an information source is required to determine its capacity to produce information. A modern identification sensor will produce a series of declarations based on a set of probabilities that describe the performance of that sensor. This is considered to be a stochastic process, which is critical in the construction of the identification vector.

IFF, ESM, and NCTR all contribute to the identification vector (represented by figure 1). The mathematical form of each type is defined by a modulation equation that is bounded by Shannon information limits. Therefore, a finite amount of information content is available from each sensor type. For a MK XII IFF interrogator this equates to the pulse position modulation (PPM) equation [Schuck *et al.*, 2000]:

$$x_{IFF}(t) = \sum_{n=0}^{N} \left| A \cos(t\omega + nt_n\omega) \right| \tag{3}$$

where: N = number of cosines necessary for pulse shaping
A = pulse amplitude (constant)
t_n = pulse pair spacing depending on mode (1, 2, 3/A, C)

From this it is possible to get various octal codes that correlate to specific aircraft object types. The set of all possible transponder reply pulses is shown in figure 5 (from two closely spaced transponders).

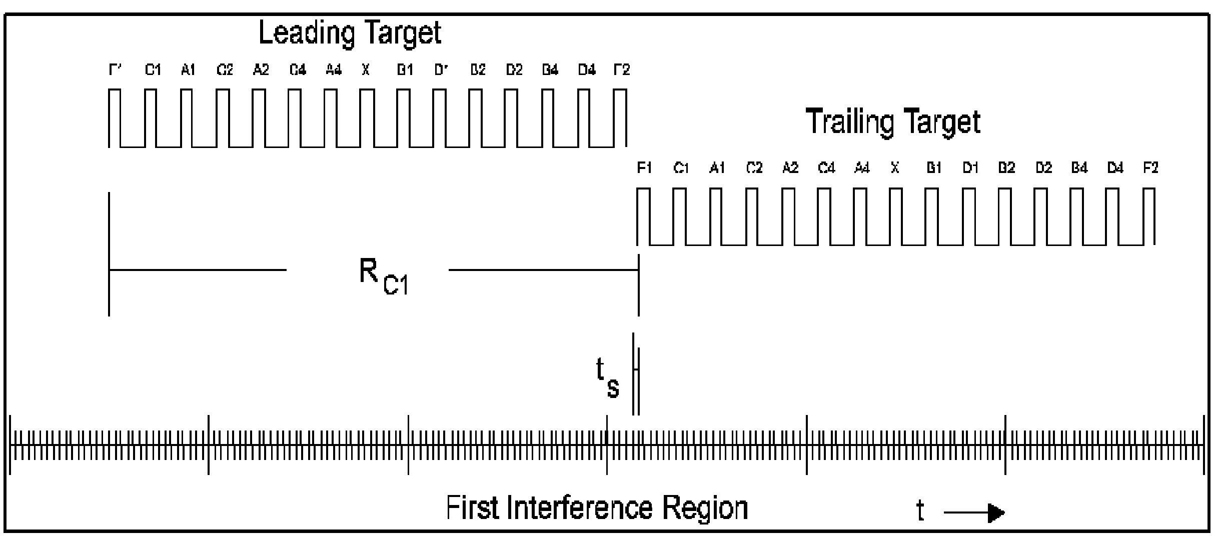

Figure 5. IFF Transponder Replies from Two Objects

For ESM, a typical signal can be of the type (among others):

$$x_{ESM}(t) = A_c[1 + k_a m(t)\cos(2\pi f_c t)] \qquad (4)$$

where: A_c = carrier amplitude
k_a = modulation index
$m(t)$ = message signal
f_c = carrier frequency

These signal characteristics can describe an emitter frequency, mode, PRF, polarization, pulse width, coding, etc. From this information, platform associations can be made.

For NCTR, one possible method to identify helicopters exploits the radar return modulation caused by the periodic motion of the rotor blades. The equation for radar cross section (RCS) as a function of angle (θ) is shown in equation(5) [Bullard and Dowdy, 1991][Misiurewicz *et al.*, 1998]:

$$RCS(\theta) = \exp(i\omega t)\frac{c}{2i\omega\tan(\theta)}\left(1 - \exp\left(\frac{2i\omega l}{c}\sin(\theta)\right)\right) \qquad (5)$$

This is illustrated in figure 6.

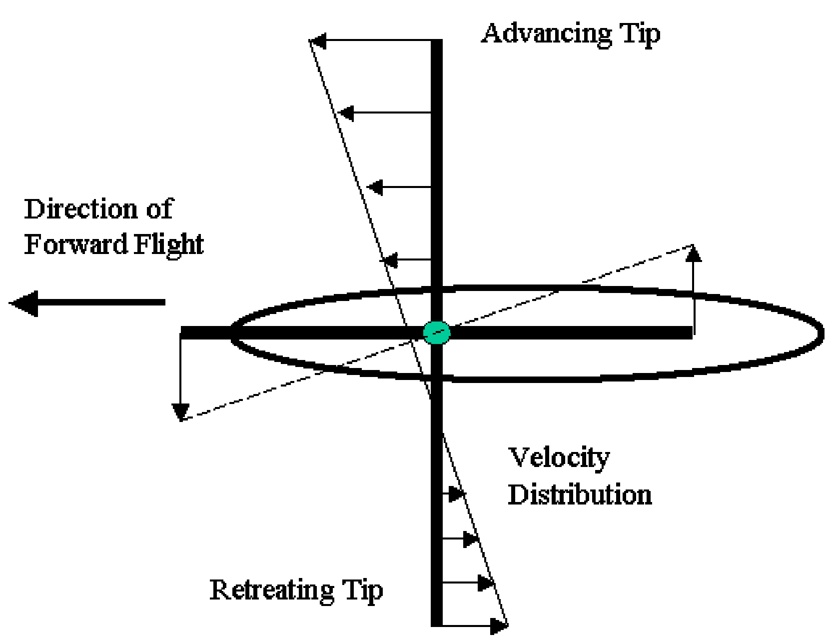

Figure 6. Feature Detection from Rotating Helicopter Blades

From the spectra described by the Fourier transform of equation (5), it is possible to determine main rotor configuration (single, twin, etc.), blade count, rotor parity, tail rotor blade count and configuration (cross, star, etc.), and hub configurations.

The purpose of these illustrations using equations (3), (4), and (5) is to show that all sensors function like a communications system and it is important to look at the amount of information that can be produced by these processes.

4. Choice, Uncertainty, and Entropy for Identification

So far, this paper has discussed the identification system and feature identification vectors (parameters) that can be created for an object, specifically an airborne object. There is a need still to measure the (a) amount of information present in an identification vector and the (b) amount of dissonance between the components of it prior to and after applying it to a fusion process.

Shannon helps in this area when he states that *if the number of messages (or "features") in the set is finite then this number or any monotonic function of this number can be regarded as a measure of the information produced when one message is chosen from the set, all choices being equally likely*. So, still following Shannon, let $H(p_1, p_2, \ldots, p_n)$ be a measure of how much "choice" there is in a selection of an event or "feature". This should have the following properties:

- H is continuous in the probabilities (p_i)
- If $p_i = 1/n$, then H is a monotonic increasing function of n. Thus with equally likely events there is more choice (uncertainty) when there are more possible events.
- If a choice is broken down into two successive choices, the original H should be the weighted sum of the individual values of H. This is illustrated in figure 7.

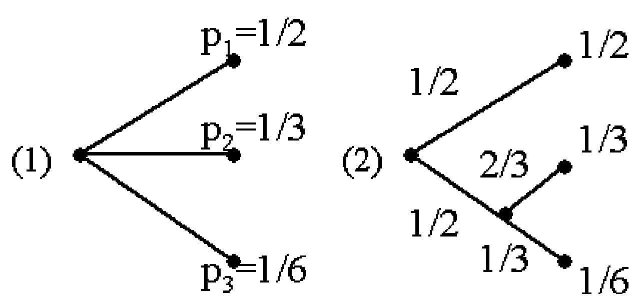

Figure 7. Decomposition of Choice

Referring to figure 7 (2), if one choice is F/A-18, successive choices of F/A-18A, F/A-18C, F/A-18D, and F/A-18E can be made, which is described in section 5. The three probabilities in (1) are (1/2, 1/3, 1/6). The same probabilities exist in (2) except that first a choice is made between two probabilities (1/2, 1/2), and the second between (2/3, 1/3). Since these are equal, the equality relationship is shown as equation 6.

$$H\left(\frac{1}{2},\frac{1}{3},\frac{1}{6}\right) = H\left(\frac{1}{2},\frac{1}{2}\right) + \frac{1}{2}H\left(\frac{2}{3},\frac{1}{3}\right) \qquad (6)$$

Shannon concludes with H the measure of *information entropy* of the form:

$$H = -K\sum_{i=1}^{n} p_i \ln p_i \qquad (7)$$

where K = positive constant.

The Shannon limit (average) is the ratio of C/H, from equations (2) and (7) respectively, which is the entropy of the channel input (per unit time) equal to that of the source. However, a problem still lies in determining how to apply entropy to disparate information sets. Sudano [Sudano, 2001] derived a solution described as the Probability Information Content (PIC) metric that provides a mechanism to measure the amount of total information or knowledge available to make a decision. A PIC value of zero (0) indicates that all choices have an equal probability of occurring and only a chance decision can be made with the available information set(s) (maximum entropy). Conversely, a PIC value of one (1) indicates complete information and no ambiguity present in the decision making process (minimum entropy). If there are N possible hypotheses (choices) $\{h_1, h_2, \ldots, h_N\}$ with respective probabilities $\{p_1, p_2, \ldots, p_N\}$, then the PIC is defined as:

$$PIC \equiv 1 + \frac{\sum_{i=1}^{N} p_i \ln p_i}{\ln N} \qquad (8)$$

The output of the PIC is intuitively similar to Shannon entropy in (7), but is now normalized to run from 0 to 1. The following example demonstrates the utility of the PIC for identification and incorporates the supporting use of a conflict measure for quantifying information dissonance.

5. Example of Identification Information Measurement

This example employs the modified Dempster-Shafer (D-S) methodology first described by Fixsen and Mahler [Fixsen and Mahler, 1997 (prepublication 1992)] and then implemented by Fister and Mitchell [Fister and Mitchell, 1994]. A set of attribute sensor data is given in table 1.

	Sensor 1		Sensor 2	
Reported Mass Distribution	F/A-18	(0.3)	F/A-18	(0.2)
	F/A-18C	(0.4)	F/A-18C	(0.4)
	F/A-18D	(0.2)	F-16	(0.2)
	Unknown	(0.1)	Unknown	(0.2)
Belief, Plausibility Evidential Intervals	F/A-18	[0.9, 0.9]	F/A-18	[0.6, 0.6]
	F/A-18C	[0.4, 0.7]	F/A-18C	[0.4, 0.6]
	F/A-18D	[0.2, 0.5]	F-16	[0.2, 0.2]
	F/A-18C or F/A-18D	[0.6, 0.9]	Unknown	[0.2, 0.2]
	Unknown	[0.1, 0.1]		

Table 1. Attribute Sensor Data from Two Sources with Computed Belief/Plausibility Intervals

The following formulas are used to derive the combined distributions and agreements. First, the *combined mass function* m_{12} is defined as:

$$m_{12} = m_1(a_1)m_2(a_1) \tag{9}$$

where $m_1(a_1)$ and $m_2(a_1)$ are the singleton mass functions from two separate sensors describing object a_1.

The *combined agreement function* $\alpha(P_1, P_2)$ is:

$$\alpha(P_1, P_2) = m_{12}\frac{N(P_1 \wedge P_2)}{N(P_1)N(P_2)} \tag{10}$$

The following explain equation (10):

- P_1 is proposition 1 and contains the list of sensor 1 declarations and masses:
  $P_1(a_i)) = \{$(F/A-18, 0.3), (F/A-18C, 0.4), (F/A-18D, 0.2), (unknown, 0.1)$\}$
- P_2 is proposition 2 and contains the list of sensor 2 declarations and masses:
  $P_2(a_j)) = \{$(F/A-18, 0.2), (F/A-18C, 0.4), (F-16, 0.2), (unknown, 0.2)$\}$
- $N(P_1)$ and $N(P_2)$ are equal to the number of elements in the "truth" set which satisfies the description given by P_1 and P_2 respectively.
- $N(P_1 \wedge P_2)$ is equal to the number of elements in the "truth" set that satisfies the description given by the combination (denoted by ^) of P_1 and P_2.

The *normalized combined agreement function* r_{ij} is,

$$r_{ij} = \frac{\alpha(P_1(a_i), P_2(a_j))}{\alpha(B, C)} \tag{11}$$

and the *normalizing factor* $\alpha(B, C)$ (the summation of all of the combined mass functions) is:

$$\alpha(B, C) = \sum_{1}^{n} \alpha(P_1, P_2) = \sum_{i,j=1}^{n} \alpha(P_1(a_i), P_2(a_j)) \tag{12}$$

The combined distributions are contained in table 2.

Sensor 1	Sensor 2	(1,1,1,0,0) F/A-18 m_i = 0.2 N = 3	(0,1,0,0,0) F/A-18C m_i = 0.4 N = 1	(0,0,0,1,0) F-16 m_i = 0.2 N = 1	(0,0,0,0,1) Unknown m_i = 0.2 N = 1
(1,1,1,0,0) F/A-18 m_j = 0.3 N = 3	Comb Object m_{ij} = $\alpha(B_i,C_j)$= r_{ij} =	(1,1,1,0,0) 0.2 x 0.3 3/3 x 3 .02/.28= **0.071**	(0,1,0,0,0) 0.4 x 0.3 1/1 x 3 .04/.28=**0.142**	(0,0,0,0,0) 0.2 x 0.3 0/1 x 3 0	(0,0,0,0,0) 0.2 x 0.3 0/1 x 3 0
(0,1,0,0,0) F/A-18C m_j = 0.4 N = 1	Comb Object m_{ij} = $\alpha(B_i,C_j)$= r_{ij} =	(0,1,0,0,0) 0.2 x 0.4 1/3 x 1 .027/.28=**0.096**	(0,1,0,0,0) 0.4 x 0.4 1/1 x 1 .16/.28=**0.571**	(0,0,0,0,0) 0.2 x 0.4 0/1 x 1 0	(0,0,0,0,0) 0.2 x 0.4 0/1 x 1 0
(0,0,1,0,0) F/A-18D m_j = 0.2 N = 1	Comb Object m_{ij} = $\alpha(B_i,C_j)$= r_{ij} =	(0,0,1,0,0) 0.2 x 0.2 1/3 x 1 .013/.28=**0.046**	(0,0,0,0,0) 0	(0,0,0,0,0) 0	(0,0,0,0,0) 0
(0,0,0,0,1) Unknown m_j = 0.1 N = 1	Comb Object m_{ij} = $\alpha(B_i,C_j)$= r_{ij} =	(0,0,0,0,0) 0	(0,0,0,0,0) 0	(0,0,0,0,0) 0	(0,0,0,0,1) 0.2 x 0.1 1/1 x 1 .02/.28=**0.071**

Table 2. Dempster-Shafer Combined Distributions

The ordered elements for each entry (F/A-18, F/A-18C, F/A-18D, F-16, Unknown) show the membership each element has with the other elements, as described in section 4 (figure 7). For example, the F/A-18 is also composed of F/A-18C and the F/A- 18D, so its truth set is (1, 1, 1, 0, 0). The total mass and belief/plausibility for each platform type/class is calculated from table 2 and shown in table 3.

Object	Total Mass	Evidential/Credibility Interval
F/A-18	0.071	[0.93, 0.93]
F/A-18C	0.142 + 0.096 + 0.571 = .809	[0.81, 0.88]
F/A-18D	0.046	[0.05, 0.12]
Unknown	0.071	[0.07, 0.07]

Table 3. Total Object Mass and Belief/Plausibility Intervals

Converting the mass assignments in table 3 using a Smets pignistic probability [Sudano, 2001] and assuming that multiple independent sensor reports of information identical to table 3 are available, then the following taxonomic identifications, PICs, and conflict measures are produced for the F/A-18C with truth set (0, 1, 0, 0, 0).

Iteration	Probability of (0, 1, 0, 0, 0)	PIC	Fister Self Conflict PD	Fister Inconsistency-B
0	0.5000	0.6161	0.3400	0.4757
1	0.8333	0.6161	0.2098	0.5767
2	0.9496	0.8512	0.0820	0.4497
3	0.9822	0.9396	0.0327	0.3062
4	0.9930	0.9730	0.0136	0.2111

Table 4. Probabilities, PICs, and Conflict Measures for Object F/A-18C

This information is represented in figure 8.

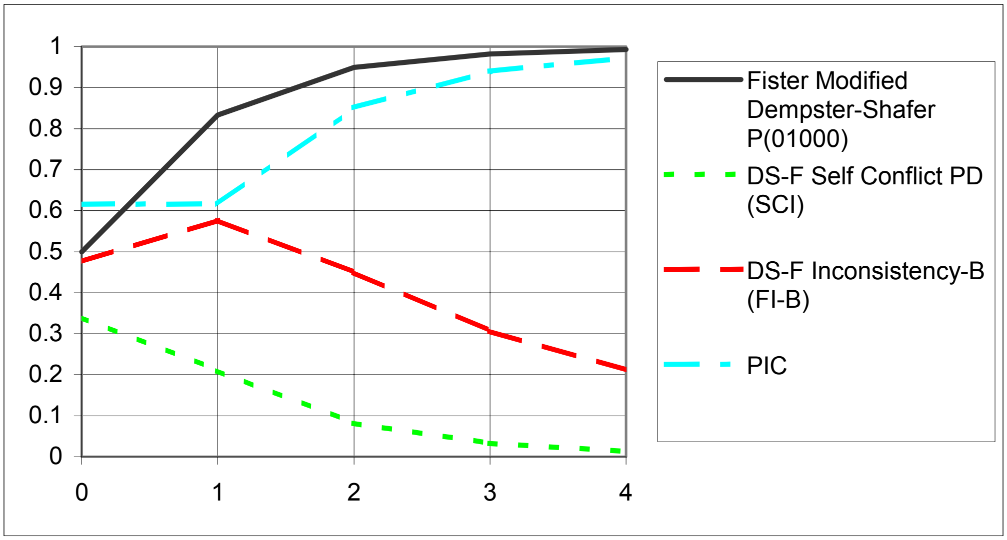

Figure 8. Chart of Probabilities, PICs, and Conflict Measures for Object F/A-18C

The solid line in the graph represents the probability that the object being reported by sensors 1 and 2 is an F/A-18C. After iteration 4, the cumulative probabilities level out at a high probability of occurrence. At the same time the PIC also grows towards 1 as more evidence is accumulated. Conversely, both the FI-B and SCI indices are being reduced. The SCI is a measurement of the amount of conflict in the information sets that support F/A-18C from each iteration without regard to evidence for other objects. In other words this is a self-similarity measurement. The FI-B index measures the amount of information conflict across the set of taxonomic identification probabilities of the F/A-18C to the F/A-18D, F/A-18, F-16, and Unknown in this example. The conflict measurement algorithms used in this example are proprietary and will be discussed in depth in the future after additional work is completed. *A priori* or dynamic thresholds can be applied to these information sets in order to determine when enough information is held and conflict reduced in order to declare the taxonomic identification of an object.

6. Applications for Network-Centric Identification

The information approach presented in section 5 lends itself well to the construction of a true nodal network-centric architecture. Figure 9 depicts a notional 7 - node architecture that allows for communication to occur in any direction between nodes that are linked.

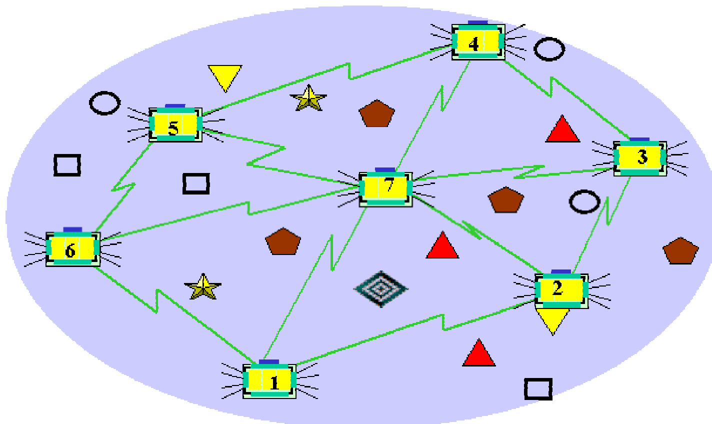

Figure 9. Notional 7 - Node Network Architecture

The various shapes that exist represent various kinds of objects that can be detected, tracked, and identified within the sphere of influence of the network. Referring back to the example in section 5, imagine that the multi-diamond object between nodes 1, 2, and 7 is the same object that is being identified from section 5 (i.e. F/A-18, F/A-18C, etc.). Since each of the seven nodes has its own unique set of organic sensors, it is assumed that the information leading to a declaration of taxonomic identity discussed in section 5 is taking place in node 1. However, both nodes 7 and 2 also have identification information on the same object because it is within their identification sensor performance envelope. If each node has the same set of identification algorithms, a hypothetical set of shared information being reported could be observed as shown in figure 10.

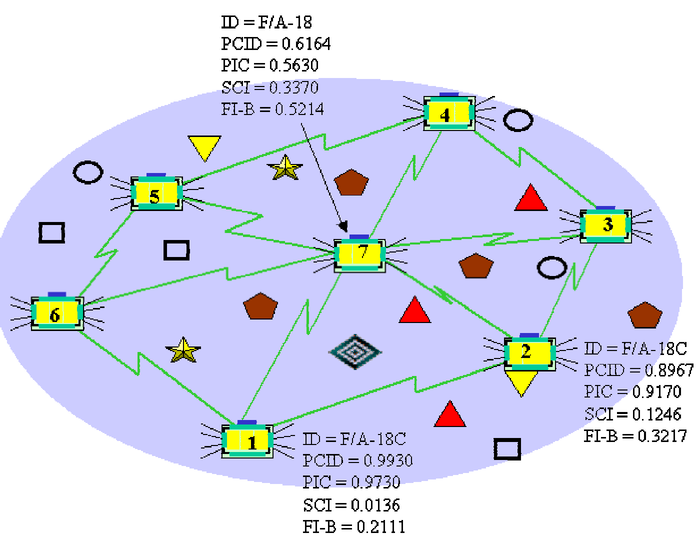

Figure 10. Identification Information Content Across Nodes 1, 2, and 7

Clearly, in this example, node 1 has the highest information content on the object, with the least amount of self-conflict or inconsistency between information sets. In this case the F/A-18C taxonomic identification would be accepted as the network identification as reported by node 1. This would happen without utilizing additional bandwidth by sending identification sensor information over the network. In cases where the there is more conflict between nodes, specific sensor information could be pulled across the network as necessary to feed the algorithms in nodes that are missing specific types of information. As an example, node 2 may have good NCTR derived information but little else due to poor geometry to the track, sensor casualties, jamming, etc. In this case its ability to declare a correct ID (PCID) is poor and much conflict could be measured via the PIC, SCI, and FI-B indices. The NCTR information obtained from the node 2 sensors could be provided via an information pull request for nodes 1 and 7 and fused accordingly. The resultant identification vector could then be broadcast with new PIC, SCI, and FI-B indices as appropriate.

7. Conclusions

This paper presented the correspondences of identification principles to Shannon communication theory that demonstrate the utility of Shannon theory to address the problem of subsurface, surface, airborne, and space-based object identification. Shannon principles applied to an identification system enable the calculation the value and dissonance of inputted information. For the generation of the identification vector, it is critical that disparate sources of information from the IFF, ESM, and NCTR domains be available. The design of an identification system according to these principles will help to eliminate many of the problems that have plagued the realization of a complete and accurate identification picture, for both individual platforms and across a networked battleforce.

The author wishes to specifically thank John Sudano, Mark Friesel and J. Bockett Hunter, all of Lockheed Martin NE&SS-SS, for their inputs to this manuscript.

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